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Transportation Research Procedia 14 (2016) 2289 – 2296

Transportation Research Procedia

www.elsevier.com/locate/procedia

6th Transport Research Arena April 18-21, 2016

Evaluating bluetooth and Wi-Fi sensors as a tool for collecting bicycle speed at varying gradients

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Abstract

The wide applications of mobile units with communication technology opens up new possibilities in data collection among road users. Sensors detecting Bluetooth and WiFi units have been successfully applied in collecting travel times from motorized vehicles. The same technology could potentially be applied to bicycle transport. As part of a policy for facilitating sustainable transport modes, more knowledge about bicyclists is needed.
This paper presents a study answering two research questions: 1. Will the use of Bluetooth and WiFi sensors provide reliable travel time data from bicyclists? 2. How are bicycle section speeds affected by different gradients?
To answer the first research question a two step test was set up to validate the equipment. Each equipment set consisted of one Bluetooth sensor and one WiFi sensor. Two sets of equipment were placed along a bicycle path with a distance of 550 meters between them. There was no adjacent road, ensuring only bicyclists and pedestrians would be registered.
Firstly, a controlled test was conducted with known Bluetooth and WiFi units brought by test cyclists. The test took place nighttime to avoid disturbance from other travelers. To validate the measured travel times, actual travel times were also registered manually. The test concluded that travel times based on Bluetooth were more accurate than travel times based on WiFi. However, both sensors provided travel times that were not significantly different from the actual ones.
Secondly, an open test was conducted along the same cycle path section during rush hours to find the penetration rate (i.e. the number of registered travel times divided to the total number of passing bicyclists), and to manually register all travel times to see whether the registered travel times were representative of the travel times for all passing bicyclists. The test showed that to reduce the variance in the registered data in order to calculate a valid average travel time, a minimum of 20 observations were needed. The test further showed that more than 90% of the registered travel times were detected by the WiFi unit.

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Peer-review under responsibility of Road and Bridge Research Institute (IBDiM)
doi:10.1016/j.trpro.2016.05.245

The second research question was addressed by selecting 7 road sections with average gradients varying from 0.5% to 9.2%, using section lengths between 500 to 1500 meters. A total of approximately 2400 travel times were registered, giving the following main findings: The average speed varied from 22.4 km/h to 8.6 km/h uphill according to increasing gradient. The variance is reduced by increasing gradient. When cycling downhill the average speed varies between 21.3 km/h and 36.5 km/h, registering the highest speed at 5.4% gradient, showing that bicyclists choose lower speeds on steep downhills. The variance seems unaffected by the gradient.
Based on this study, sensors using Bluetooth and WiFi technology can be recommended as tools to collect travel times from bicycle traffic. However, some important prerequisites are needed: the sensor locations have to be carefully chosen, as do appropriate filtering of data to avoid inclusion of pedestrians and motorists in the dataset.

Peer-review under responsibility of Road and Bridge Research Institute (IBDiM)

Keywords: Bicycle; travel speed; bluetooth; WiFi; gradient

1. Introduction

Collecting data on bicycle speed may have many purposes. More knowledge about bicycle traffic is generally needed in order to facilitate current and future cyclists as best possible. As part of a sustainable mobility strategy to increase bicycle shares, speed data can be utilized in recommendations for planning optimal infrastructure solutions, as well as in transportation demand modelling. In both cases, the fact that bicycle speeds vary between uphill and downhill should be taken into consideration. Knowledge of how different gradients affect bicycle speed is therefore required.

The recent development in mobile communication technologies brings new possibilities for data collection in traffic. Sensors detecting Bluetooth and WiFi signals have both proven successful in collecting speed data from motorized traffic. Two or more sensors placed roadside identify and recognize mobile units when passing, registering travel time and thus making it possible to calculate section speed between the sensors. There are, however, some limitations and challenges with both technologies. Both depend on passing vehicles and persons to carry discoverable mobile units with Bluetooth or WiFi enabled. Since this is not the case for all passing, the data collected will only represent a share of passing vehicles and persons carrying such units. Bluetooth detection is mainly influenced by the total number of units inside the sensors detection zones, as well as the speed of the passing unit. The more units present, and the lower passing speed, the higher detection rate. Despite these limitations, according to previous studies, the data registered by Bluetooth sensors are within sufficient reliability levels in order to provide representable travel data for section speeds for motorized traffic (Araghi et al. 2013, Araghi et al. 2012) and for bicyclist (Mei et al. 2012). WiFi detection is also affected by the same factors. High speed lowers the detection rate. Interference with other wireless signals may also reduce detection (Abbott-Jard et al. 2013, Flickenger et al. 2008).

The effect of gradient on bicycle speed has been examined in previous studies. Wilson et al. (2004) looked into the power needed to overcome physical factors when cycling at given speeds. In addition to decreasing speed by increasing gradient, they found that air drag is most influential at high speeds while rolling resistance influences low speeds the most, and that tailwind increases speed while headwind reduces speed. In an experiment, Navin (1994) found reduced speeds for comfortable cycling for both children and young males with increasing gradient. Another study in which point speed among passing cyclists at selected hills with different gradients were registered, found speeds varying between 10 and 20 km/h uphill at grade 2-3%, and downhill variations between 25 and 45 km/h (Sørensen 2011).

This paper is based on a study with dual scope, focusing on both the quality of bicycle speed data detected by Bluetooth and WiFi sensors and on bicycle speed at different gradients. Two research questions have been raised: *1.Will the use of Bluetooth and Fi sensors provide reliable travel time data from bicyclists? 2.How are bicycle section speeds affected by different gradients?* It was of special interest to investigate whether there would be any threshold gradients at which speed converged, both uphill and downhill. A sensor equipment set with both Bluetooth and WiFi sensors was investigated in this study.

This paper is structured in the following way: The first research question is addressed in section 2 and the second research question is addressed in section 3. Conclusions and recommendations for future research is presented in section 4.

2. A two-step test of Bluetooth and WiFi sensors

In order to investigate whether the Bluetooth and WiFi sensors produced reliable travel time data from cyclists, a two-step test was performed to study the penetration rate and the accuracy of the registered travel times. The first test was a controlled test where test cyclists brought known mobile units with Bluetooth and WiFi enabled. The second test was an open test performed in real traffic. Both tests took place along a cycle path with no adjacent road, ensuring only cyclists and pedestrians to be registered. Two sets of equipment were placed with a distance of 550 meters between them.

2.1. Controlled test

The controlled test took place during nighttime to avoid other cyclists interfering. Test cyclists travelled back and forth the test section 25 times, bringing a variety of mobile Bluetooth and/or WiFi enabled units (mobile phone, camera, remote control, portable sound speaker, PC mouse) in their pockets, giving a total number of 91 “unit trips”. The travel times were recorded manually and subsequently compared to those registered by the sensors.

A total number of 91 “unit trips” were conducted, 42 and 49 trips respectively with active WiFi units and Bluetooth units. In this test, the WiFi sensor detected 38.1% of the passing unites while the Bluetooth sensor detected 73.5%. Mean travel time from the manual registrations was 102 sec (SD=18.6). The WiFi sensor measured somewhat higher travel times, mean travel time found to be 112.6 sec (SD=19.0), while the Bluetooth sensor measured a mean travel time of 100.3 sec (SD=20.0). Figure 1 shows how the sensor measurements deviate from the manual registrations, demonstrating the highest deviations from the WiFi registrations. However, none of the differences in mean travel time between the manual and sensor registrations were significant.

2.2. Open test

The open test was performed in real traffic during peak hours on a given day. Both passing cyclists and pedestrians were registered manually. In order to separate the bicycles from the pedestrians in the sensor data, a filtering routine was implemented. Based on previous speed registrations among cyclists (Overå 2013), mobile units passing with speeds in the interval between 13-40 km/h were identified as cyclists, while units travelling at lower speeds were identified as pedestrians. A total number of 499 cyclists and 177 pedestrians were manually registered and passed the two sensor equipment sets during the test period.

Given that the manually observations represented the true number of passing cyclists and pedestrians, the test revealed a penetration rate of 19.5% for cyclists and 33.8% for pedestrians. Of the 85 travel times detected by the sensors, only one registration was made by the Bluetooth sensors, all other were detected by the WiFi sensors.

Mean travel time in the morning peak hours from the manual registrations was 93.0 sec (SD=15.5), while the sensors measured 90.3 sec (SD=21.2). In the afternoon peak hours the cyclists chose higher speeds. The manual registrations found mean travel time of 80.5 sec (SD=15.5) and the sensors measured 84.3 sec (SD=25.4). These differences between the sensors and the manual registrations were not found significant.

A closer look into how the mean travel times from the sensors deviated from those found by manually registrations was done by dividing the registrations into time intervals. For each time interval the absolute value of the percent deviation was calculated. By adding up the intervals it was possible to study how the number of sensor registrations affected the deviations in mean travel time. This is shown in Figure 2. The deviations seem to stabilize below 5% when the number of observations exceeds 20.

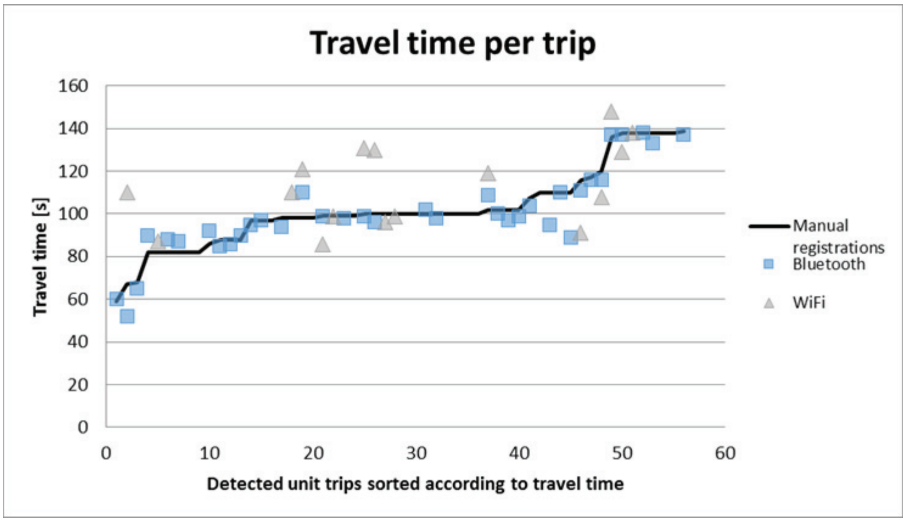

Fig. 1. Comparison between manually registered travel times (black line) and travel times registered by Bluetooth and WiFi sensors in controlled test.

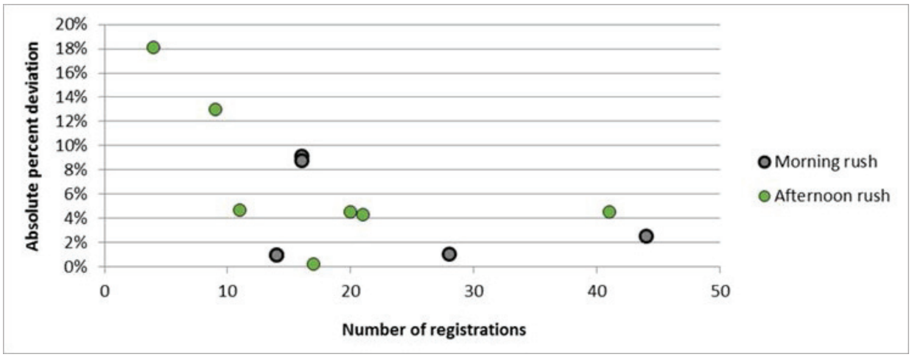

Fig. 2. Absolute percent deviations of the mean travel times derived from the sensors compared to the manually registered ones compared to the number of registrations by the Bluetooth and WiFi sensors in the open test.

2.3. Discussion

The higher detection rate found in the controlled test from the Bluetooth sensor compared to the WiFi sensor, 73.5% to 38.1%, can be explained by the nature of how these two sensor technologies perform their search for Bluetooth and WiFi units. The detection rate from the Bluetooth sensor is not too different from the one found by Araghi et al. (2013). They found a detection rate of approximately 80% among cars. The travel times registered in the open test came however almost entirely from the WiFi sensors, indicating that people in general brings very few active Bluetooth units when cycling or walking. Mei et al. (2012) also found low shares of active Bluetooth units, 2-3%, among cyclists.

In the open test a penetration rate of 20% was found among the cyclists, indicating that on average five cyclists are needed in order to make one travel time registration. The test further suggests that a minimum of 20 registrations should be collected in order to provide more reliable travel times.

The controlled test gave higher average absolute percent deviations in the travel times from the WiFi sensors than the Bluetooth sensors when comparing the sensor registrations to the manually, a finding confirming a previous study (Wang et al. 2014). The deviations will however decrease by increasing section length.

Another issue is the filtering procedure. The sensors are not able to distinguish between pedestrians, cyclists and motorists. By setting a speed limit higher than most walking speeds, passing units most probably belonging to pedestrians will be filtered out. There is however still a possibility that slow cyclists will be filtered out, and that running people will be included. Filtering motorists when the selected section is parallel to a road is more challenging since their speeds may vary within the same range as the bicycle speeds. One way of filtering out motorists is to use a triple set of equipment and locate the third set along a nearby dedicated cycle path connected to the section studied, so that a unique identification of bicycles may take place. During these tests, interfering of motorists were not an issue, since there were no adjacent roads to the bicycle path chosen for the study.

3. Measuring bicycle speed at varying gradients

The sensor equipment set containing both Bluetooth and WiFi sensors was utilized in collecting speed data from cyclists at varying gradients. Both uphill and downhill speeds were studied.

3.1. Study design

Seven road sections with varying gradients were chosen for this study. All sections had dedicated cycle paths or cycle lanes. The gradients varied from 0.5% to 9.2%. All registrations were accomplished on weekdays during spring, covering a minimum of 24 continuous hours. Filtering of the registrations was based both on speed and location. Individual considerations were made for each road section to determine the limits for which the registrations within were categorized as bicycles. These were based on a combination of the speed profiles and the share of Bluetooth registrations within each speed interval. A raised share of Bluetooth registrations indicated that there were cars included in the data set. Table 1 gives an overview of the dataset.

3.2. Results

The main results are presented in Table 1. The speeds decrease by increasing gradient when cycling uphill, as do the standard deviations. When cycling downhill, the speeds increase by increasing gradient at the lowest gradients. The highest mean speed downhill was registered at gradient 5.4%. The highest standard deviation was, however, found downhill at the highest gradient, 9.2%, reflecting the high diversity in speed choices among cyclists in steep downhill. The dispersion in speed choices is clearly demonstrated in Figure 3 and 4 by the cumulative lines.

Table 1. Registered speed uphill and downhill at varying gradients. %BT denotes the share of speeds detected by the Bluetooth sensor. *It was not possible to filter cyclists from motorists downhill at section no 6. Therefore, manually registrations were performed downhill at this section, covering one hour of morning peak.

Section	Length	Gradient	Uphill					Downhill				
	(m)	(%)	Registrations		Speeds (km/h)			Registrations		Speeds (km/h)		
			N	% BT	Mean	Median	SD	N	% BT	Mean	Median	SD
1	765	0.5	265	22	22.4	23.0	6.8	181	18	21.3	22.0	6.1
2	470	0.8	185	24	21.5	22.9	6.6	130	17	22.7	23.2	7.1
3	440	2.0	51	10	17.3	17.6	5.3	67	9	27.3	28.8	6.0
4	820	2.6	307	13	15.8	16.3	4.3	252	19	29.6	32.4	7.8
5	1580	3.2	310	16	15.7	16.1	3.8	187	25	30.3	34.1	8.6
6*	470	5.4	269	9	12.8	13.8	2.5	50	-	36.5	37.6	6.3
7	460	9.2	75	15	8.6	8.6	2.2	115	18	30.2	36.0	8.9

3.3. Discussion

The effect of gradients on uphill bicycle speed found in this study was in accordance with the expectations based on theoretical discussions of the power needed to overcome physical factors when cycling at given speeds (Wilson et al. 2004). The assumption that there might be a threshold gradient at which speeds converged did not find support from these registrations. This may be due to the selection of road sections. A possible threshold gradient might be higher than the maximum gradient included in this study. For downhill, the effect of a threshold gradient was identified. The speeds increased with increasing gradient up to 5.4%, while decreased from 5.4% to 9.2%. This effect is assumed to be a consequence of cyclists feeling insecure and experience loss of control at high speeds. The high dispersion of speeds at gradient 9.2% may thus be a manifestation of risk perception and willingness to take risks as being qualities that vary between people. There is however a rather large gap between gradient 3.2% and 9.2%. Based on this study with only one road section within this interval, it is not possible to identify at which gradient this threshold effect occurs.

The standard deviations decreased by increasing gradient uphill. This effect may be explained by cyclists having less freedom to choose speed in steep hills due to physical limitations of muscles and energy use.

The uphill mean speeds from this study were found to be lower than the ones found by Navin (1994). This may be due to Navin (1994) collecting speed data from an experiment among male university students, while the study presented here covers a wider range of cyclists. The pattern of decreasing standard deviation with increasing gradient is however comparable.

All standard deviations may have been affected by the speed filtering, since cyclists may have been filtered out due to too high or too low speeds compared to the selected limits.

The speed filtering was set individually for each road section. Although limits were carefully chosen to reduce detections of pedestrians and motorists, there is no guarantee that none of these were included in the data set. For road sections where a number of pedestrians and runners may have been detected, the mean speed may have been underestimated. Road sections with a number of detected motorists may have overestimated mean speeds. Since the lower limit was set lower for uphill cycling in the steepest hills, the probability of detecting pedestrians were higher in steep uphill. On the other hand, such biases may be outweighed by a number of E-bikes being observed in the steepest hills.

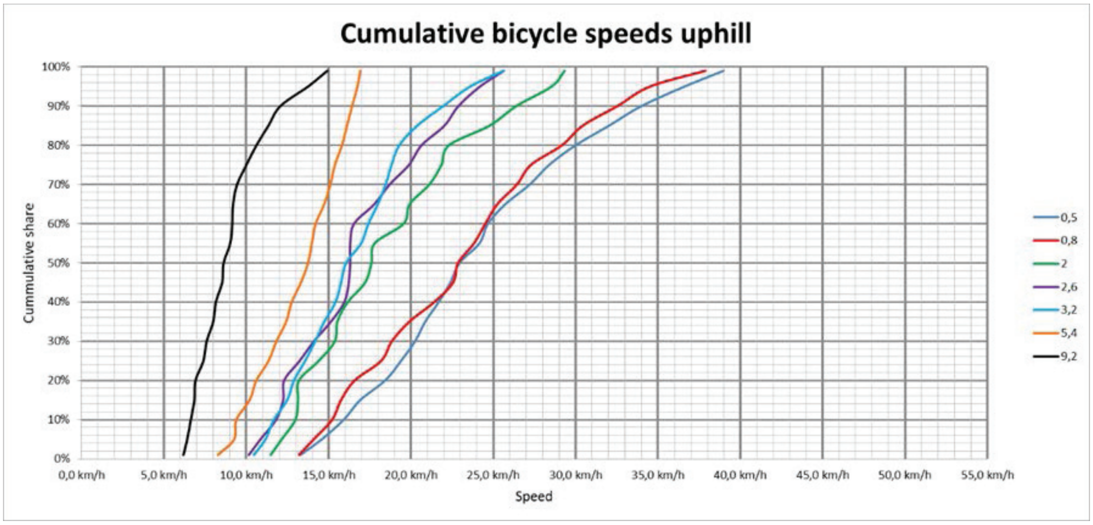

Fig. 3. Cumulative speeds uphill at varying gradients. Each colored line represents a gradient.

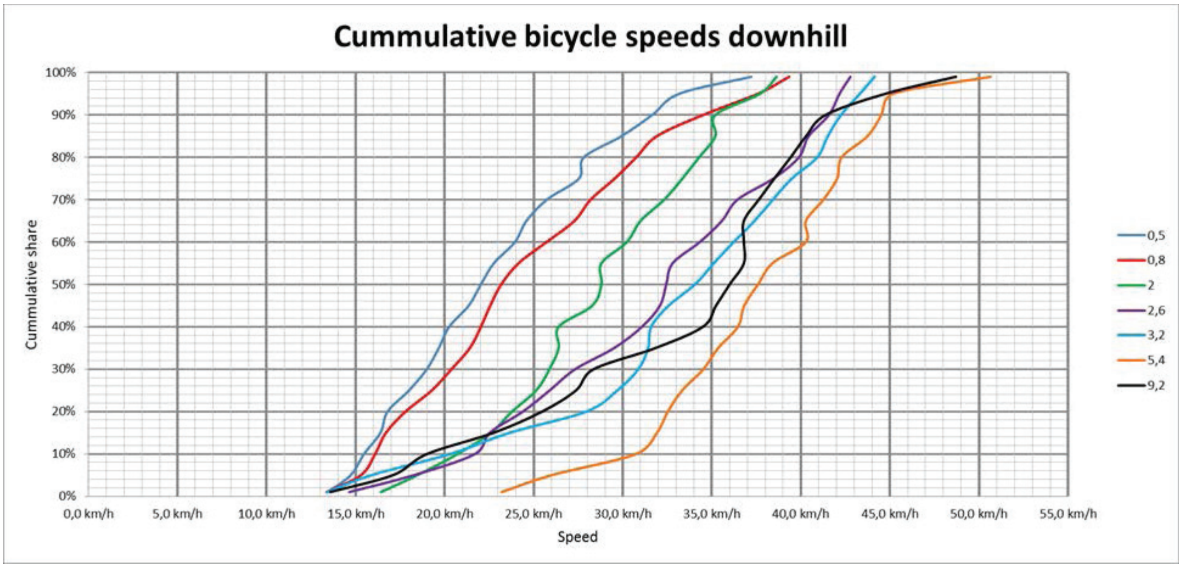

Fig. 4. Cumulative speeds downhill at varying gradients. Each colored line represents a gradient.

As shown in Table 1, the number of observations varied between the road sections from 50 to 310, thus fulfilling the recommendations of a minimum of 20 registrations suggested by the initial test of the Bluetooth and WiFi sensors. Ideally, the registration period for all road sections should have covered at least one week to cover a variety of weather and surface conditions. Due to limited time to conduct the study, only road sections with few cyclists were covered for more than one day. By looking into these data, it seems like the differences in mean speed between different days are negligible. All registrations took place in spring. The results are assumed to be representative for all seasons except winter time.

The gradients for each section represent the average gradients across the sections. When selecting road sections for this study, sections with even gradients along the whole section were demanded. In the real world, these are hard to find. The chosen road sections contains some minor variation in gradient, which may have affected the results.

The share of Bluetooth registrations were higher than expected based on the open test. Three of the sections had shares exceeding 20%, indicating that motorists have not been filtered out as efficiently as expected. However, for two of these sections, location filtering was used, ensuring that no motorists were included in the data set. In the third one, section 5, the high share of Bluetooth registrations is probably due to infiltration of motorists in the data set. This may have affected the results, giving a somewhat higher mean speed downhill than the correct one.

4. Conclusions and recommendations for future research

A two-step test was conducted in order to answer the first research question: *Will the use of Bluetooth and WiFi sensors provide reliable travel time data from bicyclists?* Based on the test, and the given local conditions, such as the selected section length and the roadside placement of the equipment, this study concludes that the use of Bluetooth and WiFi sensors will provide reliable travel time data from bicyclists. Despite a penetration rate of 20%, the mean travel times registered by the Bluetooth and WiFi sensors were not significantly different from the manually registered mean travel times from all passing bicycles. However, the analysis suggests that a minimum of 20 registrations is recommended in order to provide reliable results.

Thereafter, these sensors detecting Bluetooth and WiFi units were used to answer the second research question: *How are bicycle section speeds affected by different gradients?* The speed registrations at seven road sections at varying gradients confirmed that bicycle speed is affected by varying gradients. At gradients close to zero, the mean speed is found to be 21-23 km/h. The speed decreases by increasing gradient uphill, as do the standard deviations.

Mean speed uphill at gradient 9.2% is found to be 8.6 km/h. Downhill the findings suggest that there exists a threshold gradient. Speeds increase with increasing gradient downhill until this threshold reaches. For gradients exceeding this threshold, the speeds decrease. The highest mean speed downhill, 36.5 km/h was found at gradient 5.4%, while mean speed at gradient 9.2% was found to be 30.2 km/h. Based on the selection of road sections included in this study, it was not possible to make an exact identification of this threshold gradient value.

The biggest challenge when collecting bicycle speed data from Bluetooth and WiFi sensors is to succeed in filtering. An optimal filtering should exclude pedestrians and motorists from the data set, but avoid excluding cyclists. Using speed filtering only, such a task may prove impossible, since the lower range of bicycle speeds may overlap with the range of pedestrian speeds, and the higher range may overlap with the range of motorized speeds. This is especially so at high gradients, with overlap with pedestrians uphill and motorists downhill. Thus, location filtering may in many cases prove necessary. By placing one of the sensors, or a third additional sensor, along a dedicated cycle path separated from the road with motorized traffic, it is possible to filter out the speeds of motorists. A successful filtering of pedestrians is however in most cases still dependent on appropriate speed filtering.

Based on this study, sensors using Bluetooth and WiFi technology can be recommended as tools to collect travel times from bicycle traffic. However, some important prerequisites are needed: The sensor locations have to be carefully chosen, as do appropriate filtering of data to avoid inclusion of pedestrians and motorists in the dataset.

This study may be followed up in several ways. One interesting path is to include more road sections with gradients in the interval between 3.2% and 9.2% in order to identify the threshold gradient at which the mean downhill speed reaches its maximum. The influence of weather conditions on bicycle speeds in general and at varying gradients is another interesting continuation of this research. It would also be interesting to look into varying gradients at different infrastructure solutions, such as cycle lanes vs cycle paths, to see if speeds vary between them. Another path is to replicate this study in other regions or countries to assess the validity of these results. Further research to identify any minimum distance between the sensors in order to provide reliable results is also welcomed.

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